For Online Publication

LABORATORY MEASURE OF CHEATING PREDICTS SCHOOL MISCONDUCT*

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Online Appendix

Contents:

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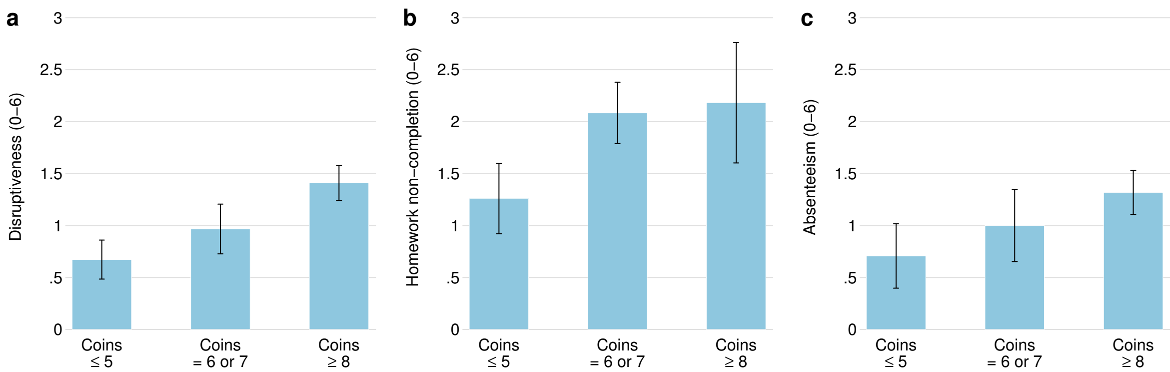
A. Additional Figures

Figure A.1: *Mobile Laboratory*

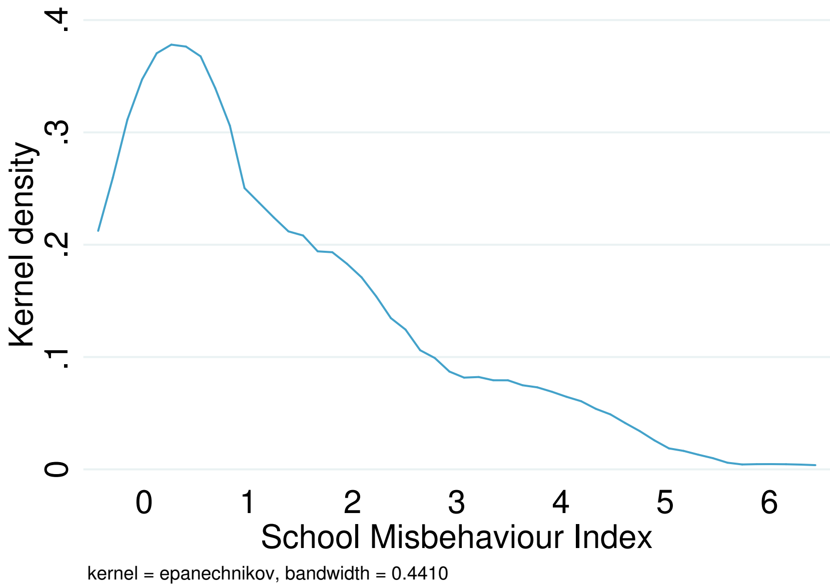
The figure shows how the mobile laboratory was set up in the classrooms. Cardboard walls were installed to shield the subjects from sight.

Figure A.2: *Behaviour in the Coin Task by Tertiles and School Misconduct*



The figure shows averages of individual measures of school misbehaviour by tertiles of coins taken in the coin task. Students who took a higher number of coins (a) disrupt the class to a larger degree, (b) fail to do their homework more often, and (c) are more frequently absent from school. Error bars indicate the standard error of the mean (adjusted for clustering at the class level).

Figure A.3: *Distribution of the School Misbehaviour Index*



The figure displays the kernel density estimate for the school misbehaviour index.

B. Additional Tables

Table B.1: *Robustness: # Reported Heads*

Dependent variable	(1) # of reported heads	(2) School Misbehaviour Index	(3)
# of reported heads		0.154**	0.144**
		(0.041)	(0.049)
Age	-0.059	0.492***	0.475***
	(0.575)	(0.005)	(0.006)
Female	-0.926***	-0.639**	-0.684**
	(0.000)	(0.015)	(0.010)
Swiss nationality	-0.457*	0.154	0.193
	(0.087)	(0.172)	(0.163)
High school	-0.786	-1.377***	-1.068**
	(0.108)	(0.009)	(0.045)
Parental education	-0.222	0.481	0.546
	(0.377)	(0.202)	(0.171)
Crystallized intelligence	-0.160		-0.256**
	(0.269)		(0.046)
Fluid intelligence	-0.015		0.037
	(0.905)		(0.798)
Constant	8.243***	-6.366***	-6.242***
	(0.000)	(0.003)	(0.003)
Observations	161	161	161
R^2	0.227	0.309	0.329

This table reports OLS coefficient estimates. p-values are reported in parenthesis. In column (1), we regress the number of reported heads on a set of individual characteristics and two measures of cognitive ability. Age is measured in years. Female, Swiss nationality, High school, and Parental education are dummy variables. Parental education equals to one if at least one parent has a university degree. Crystallized and Fluid intelligence are based on the scores from the word fluency test and the symbol-digit correspondence test, respectively. Both cognitive ability measures are normalized to have a mean of zero and a standard deviation of one. In columns 2 and 3, the dependent variable is the School misbehaviour index which is constructed by averaging the three items of school misconduct, including disruptiveness in class, failure to complete homework, and absenteeism (all measured on a scale from "never misbehaves" (= 0) to "always misbehaves" (= 6)). Because the models in columns 2 and 3 use teacher evaluations, we computed p-values that are robust to clustering at the class level. To account for the low number of clusters we applied the wild cluster bootstrap procedure (Cameron *et al.* 2008) using Webb's (2013) 6-point distribution of weights. The number of observations is 161 instead of 162 because one subject did not state his age. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.2: *Robustness: Individual Measures of School Misbehaviour*

Dependent variable	(1) Disruptiveness	(2)	(3) Homework non-completion	(4)	(5) Absenteeism	(6)
# of coins taken	0.126**	0.118**	0.164	0.154	0.161**	0.163**
	(0.031)	(0.026)	(0.126)	(0.148)	(0.013)	(0.012)
Age	0.439***	0.415***	0.598***	0.569**	0.429**	0.432**
	(0.003)	(0.005)	(0.005)	(0.010)	(0.035)	(0.040)
Female	-0.907***	-0.960***	-0.958**	-1.025**	0.004	-0.004
	(0.002)	(0.002)	(0.027)	(0.014)	(0.987)	(0.987)
Swiss nationality	0.207	0.260	0.013	0.080	0.208	0.219
	(0.307)	(0.254)	(0.945)	(0.746)	(0.496)	(0.490)
High school	-1.425***	-0.940	-1.765**	-1.188*	-0.889	-0.972*
	(0.000)	(0.193)	(0.017)	(0.054)	(0.126)	(0.081)
Parental education	0.475*	0.583**	0.404	0.531	0.507	0.482
	(0.050)	(0.017)	(0.361)	(0.248)	(0.233)	(0.246)
Crystallized intelligence		-0.374**		-0.452*		0.025
		(0.044)		(0.067)		(0.735)
Fluid intelligence		0.008		0.028		0.085
		(0.952)		(0.886)		(0.694)
Constant	-5.599***	-5.481***	-7.026***	-6.884***	-6.339**	-6.351**
	(0.004)	(0.004)	(0.004)	(0.008)	(0.023)	(0.025)
Observations	161	161	161	161	161	161
R^2	0.261	0.296	0.232	0.262	0.168	0.171

This table reports OLS coefficients estimates. p-values are reported in parenthesis. We regress each measure of school misconduct (i.e., disruptiveness in class, failure to complete homework, and absenteeism; all measured on a scale from "never misbehaves" (= 0) to "always misbehaves" (= 6)) on a set of individual characteristics and two measures of cognitive ability. Age is measured in years. Female, Swiss nationality, High school, and Parental education are dummy variables. Parental education equals to one if at least one parent has a university degree. Crystallized and Fluid intelligence are based on the scores from the word fluency test and the symbol-digit correspondence test, respectively. Both cognitive ability measures are normalized to have a mean of zero and a standard deviation of one. Because the models use teacher evaluations, we computed p-values that are robust to clustering at the class level. To account for the low number of clusters we applied the wild cluster bootstrap procedure (Cameron *et al.* 2008) using Webb's (2013) 6-point distribution of weights. The number of observations is 161 instead of 162 because one subject did not state his age. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C. Six point wild cluster bootstrap procedure

Because the regression models in column (2) to (4) in Table 1 use teacher evaluations as a dependent variable, we compute p-values that are robust to clustering at the class level. To account for the low number of clusters G we use the wild cluster bootstrap procedure (Cameron *et al.* 2008) using the six point distribution of weights proposed by Webb (2013). The procedure to compute the p-value for each coefficient separately works as follows:

From the original sample we compute the Wald statistic for the coefficient of interest β_1: $w = (\hat{\beta}_1 - \beta_0)/s_{\hat{\beta}_1}$, where $s_{\hat{\beta}_1}$ is the cluster robust standard error of the estimated coefficient $\hat{\beta}_1$. In addition we compute $\hat{\beta}^{\mathbf{R}}$ and the residuals $\{\hat{u}_1^R, ..., \hat{u}_G^R\}$ using OLS and imposing the restriction $H_0 : \beta_1 = \beta_1^0$ (i.e., we regress the measure of school misbehaviour y_{ig} on a constant and all regressors except for $x_{1,ig}$). We then iterate the following steps 1000 times:

1. We form a sample of G clusters $\{(\hat{y}_1^*, X_1), ..., (\hat{y}_G^*, X_G)\}$ as follows: For each cluster $g = 1, ..., G$ we formed $\hat{u}_g^{R*} = d_g * \hat{u}_g^R$, where the weights d_g have a 1/6 chance to take each value in the six point distribution $\{-\sqrt{1.5}, -\sqrt{1}, -\sqrt{0.5}, \sqrt{0.5}, \sqrt{1}, \sqrt{1.5}\}$. Then, we form $\hat{y}_g^* = X_g'\hat{\beta}^R + \hat{u}_g^{R*}$ for $g = 1, ..., G$.

2. We calculate the Wald statistic $w_b^* = (\hat{\beta}_{1,b}^* - \beta_0)/s_{\hat{\beta}_{1,b}^*}$ using $\hat{\beta}_{1,b}^*$ and its standard error $s_{\hat{\beta}_{1,b}^*}$ estimate from the bth pseudo sample.

Finally, we retrieve the p-value for $\hat{\beta}_1$ by computing the fraction of times $w_b^* > w$ for $b = 1, ..., 1000$.

D. Additional References

Cameron, A.C., Gelbach, J.B. and Miller, D.L. (2008). 'Bootstrap-based improvements for inference with clustered errors', *Review of Economics and Statistics*, vol. 90(3), pp. 414–427.

Webb, Matthew, D. (2013). 'Reworking wild bootstrap based inference for clustered errors', Working Paper No. 1315, Queen's Economics Department.